UNIVERSITI PUTRA MALAYSIA

ARTIFICIAL INTELLIGENCE-BASED TOOL CONDITION MONITORING IN ROBOTIC INCREMENTAL SHEET FORMING THROUGH VIBRATION, TOOL WEAR AND SURFACE ROUGHNESS ANALYSES

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By

NAZARUL ABIDIN BIN ISMAIL

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

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Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

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Chair: Assoc. Prof. Mohd Idris Shah Bin Ismail, PhD
Faculty: Engineering

Sheet metal forming is a fabrication process that allows sheet metal to be formed in 3D shapes with the use of a specific tool and die. However, the conventional sheet metal forming has disadvantages in terms of quality and low flexibility, and it also prolongs the time-to-market in producing low costs prototype products. Robot-based incremental sheet forming (ISF) is a new prospect and one of the relatively new sheet metal forming processes to fabricate a product with 3D complex shapes. Interests in new techniques with a variety approach for forming processes have created more studies by researchers on the robot-based ISF process. However, tool wear always makes the difficulty of the ISF process for sustaining the process performance. In the present study, the development of a comprehensive predictive model for tool wear in robot-based ISF using artificial intelligence (AI) has been conducted. The model would predict the critical degradation of tool wear and simultaneously the relationship with quality of the formed workpiece surface. The robot-based ISF experiments were carried out using a forming tool of AISI D2 tool steel with a 10 mm diameter that attached to the ABB IRB 4400/60 IRC5 industrial robotic arm. Three different materials of SUS316 stainless steel, Cu60Zn40 copper alloy and AA3003 aluminum alloy with 0.5 mm thickness were used as workpieces. As preliminary experiments, a parametric optimization was carried out to determine optimum processing parameters in robot-based ISF using L18 orthogonal array design of experiments. The vibration signals of the ISF process were recorded by the accelerometer sensors, which are located on the forming tool and workpiece. Subsequently, after the vibration signals through signal processing, pattern recognition was conducted to identify and categorize the tool condition by two clusters, which are a tool in good condition and worn out. The increasing of surface roughness on the workpieces can also be seen noticeably with the increasing of vibration on the forming process due to tool wear. This proving that vibration signals can provide the tool wear identification for the ISF process. The predictive models were developed and compared between three different AI models, which are artificial neural network (ANN), fuzzy logic (FL) and adaptive network-based fuzzy inference system (ANFIS). The prediction using ANN model with two hidden layers showed that it has an excellent prediction accuracy of 99.94 % for tool wear (architecture 2-4-4-1) and 91.77 % (architecture 2-5-3-1) for surface roughness. The use of the ANN with two hidden layers is the best model to predict the tool wear in robot-based ISF. The successful development of prediction of tool wear in robot-based incremental sheet forming can provide a significant way in tool condition monitoring system to minimize downtime related with tool damaged and affected the quality of the workpieces.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PEMANTAUAN KEADAAN ALAT BERASASKAN KECERDASAN TIRUAN DALAM PEMBENTUKAN LEMBAR PENINGKATAN BERBASIS ROBOT YANG MEMBENTUK MELALUI GETARAN, KEHAUSAN ALAT DAN ANALISIS KEKASARAN PERMUKAAN

Oleh

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Pembentukan kepingan logam kepada bentuk tertentu adalah proses fabrikasi yang memungkinkan kepingan logam terbentuk dalam bentuk 3D dengan penggunaan alat tertentu dan acuan. Walau bagaimanapun, pembentukan kepingan logam secara konvensional mempunyai kelemahan dari segi kualiti dan fleksibiliti yang rendah, dan ini juga memanjangkan masa ke pasaran walaupun dalam menghasilkan produk prototaip dengan kos yang rendah. Pembentukan kepingan logam berasaskan robot adalah prospek baru dan ia adalah salah satu proses pembentukan kepingan logam yang agak baru untuk membuat produk dengan bentuk yang kompleks seperti 3D. Minat dalam teknik baru dengan pendekatan yang pelbagai untuk membentuk proses ini telah membuatkan lebih banyak kajian dari penyelidik mengenai proses pembentukan kepingan logam ke bentuk tertentu berasaskan robot. Walau bagaimanapun, penggunaan alat membentuk ini menyebabkan kesukaran untuk mengekalkan prestasi proses. Dalam proses pembentukan kepingan ke bentuk tertentu, kehausan alat bergantung kepada ketebalan bahan, bahan untuk alat membentuk, bahan kerja, pelinciran, halaju dan jalur kerja. Dalam kajian ini, pengembangan model ramalan komprenhensif untuk penggunaan alat dalam proses ini yang berasaskan robot menggunakan kecerdasan buatan telah dilakukan. Model ini akan meramalkan kemerosotan kritikal kehausan alat dan pada masa yang sama perhubungan dengan kualiti permukaan benda kerja yang terbentuk. Eksperimen pembentukan kepingan logam kepada bentuk tertentu berasaskan robot dilakukan dengan menggunakan alat pembentuk keluli AISI D2 dengan diameter 10 mm yang dilekatkan pada lengan robot industry ABB IRB 4400/60 IRC5. Tiga bahan berbeza iaitu keluli tahan karat SUS316, aloi tembaga Cu60Zn40 dan aloi aluminium AA3003 dengan ketebalan 0.5 mm digunakan sebagai bahan kerja. Sebagai eksperimen awal, pengoptimuman parametric dilakukan untuk menentukan parameter pemprosesan optimum dalam eksperimen berasaskan robot menggunakan

kaedah Taguchi dengan menganalisa kekasaran permukaan benda kerja yang terbentuk. Analisis varians (ANOVA) digunakan untuk mengenal pasti parameter proses yang paling signifikan yang mempengaruhi kekasaran permukaan. Isyarat getaran proses eksperimen ini dirakam oleh sensor akselerometer, yang terletak di alat dan benda kerja. Selanjutnya, setelah isyarat getaran melalui pemprosesan isyarat, pengecaman pola dilakukan untuk mengenal pasti dan mengkategorikan keadaan alat kepada dua kumpulan, iaitu alat dalam keadaan baik dan rosak. Peningkatan kekasaran permukaan pada benda kerja juga dapat dilihat dengan bertambahnya getaran pada proses pembentukan kerana kehausan alat. Ini membuktikan bahawa isyarat getaran dapat memberikan pengenalan kehausan alat untuk proses pembentukan kepingan logam ke bentuk tertentu. Model ramalan dikembangkan dan dibandingkan di antara tiga model kecerdasan buatan yang berbeza, iaitu rangkaian saraf tiruan (ANN), logic kabur (FL) dan system inferensi kabur berasaskan rangkaian adaptif (ANFIS). Ramalan menggunakan model ANN dengan dua lapisan tersembunyi menunjukkan bahawa ia mempunyai ketepatan ramalan yang sangat baik iaitu 99.94 % untuk kehausan alat (seni bina 2-4-4-1) dan 91.77 % (seni bina 2-5-3-1) untuk kekasaran permukaan. Penggunaan ANN dengan dua lapisan tersembunyi adalah model terbaik untuk meramalkan kehausan alat dalam eksperimen berasaskan robot ini. Perkembangan kejayaan ramalan kehausan alat dalam pembentukan lembaran tambahan berasaskan robot dapat memberikan cara yang signifikan dalam system pemantauan keadaan alat untuk meminimumkan waktu henti yang berkaitan dengan alat yang rusak dan mempengaruhi kualiti benda kerja.

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In the name of ALLAH, the most Gracious and most Compassionate

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of Supervisory Committee were as follows:

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Declaration by Members of Supervisory Committee

This is to confirm that:

- the research and the writing of this thesis was under our supervision;
- supervision responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) are adhered to

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LIST OF ABBREVIATIONS

3D	Three Dimensional
A/D	Analog Digital
AA	Aluminum Alloy
AE	Acoustic Emission
AFM	Atomic Force Microscope
AI	Artificial Intelligent
AISI	American Iron and Steel Institute
ANN	Artificial Neural Network
ANFIS	Adaptive Network-based Fuzzy Inference System
ANOVA	Analysis of Variance
ASP	Analog Signal Processing
BP	Back-Propagation
CAD	Computer Aided Design
CNC	Computer Numerical Control
CMM	Coordinate Measuring Machine
DAQ	Data Acquisition
DDQ	Deep Drawing Quality
DOE	Design of Experiment
DSP	Digital Signal Processing
DWT	Discrete Wavelet Transform
EDS	Energy Dispersive
FIS	Fuzzy Inference System
FE	Finite Element
FFT	Fast Fourier Transform

FL	Fuzzy Logic
GA	Genetic Algorithm
HRC	Hardness Rockwell C
HSS	High-speed Steel
IoT	Internet of Things
ISF	Incremental Sheet Forming
ISMF	Incremental Sheet Metal Forming
JP	Japan
KUKA	Keller Und Knappich Augsburg
LS	Least Square
MEMS	Micro-Electro-Mechanical System
MSE	Mean Square Error
MUX	Multiplexer
ORB	Oblique Roller Ball
PCA	Principal Component Analysis
PID	Proportional Integral Derivative
PSD	Power Spectral Density
PSO	Particle Swarm Optimization
RB	Radial Basis
RMS	Root Mean Square
RMSE	Root Mean Square Error
RSM	Response Surface Methodology
SAE	Society of Automotive Engineering
SEM	Scanning Electron Microscope
SF	Signal Feature
SPIF	Single Point Incremental Forming

STFT	Short Time Fourier Transform
S/N	Signal-to-Noise
TCM	Tool Condition Monitoring
TCP	Tool Center Point
TPIF	Two Point Incremental Forming
TW	Tool Wear
UPM	Universiti Putra Malaysia
US	United State
WT	Wavelength Transform
XRD	X-Ray Diffraction

CHAPTER 1

INTRODUCTION

1.1 Background and Motivation

Recently, the production of sheet metal forming is rapidly increased due to customer demand concerning more personalized products and the requirement of smaller batches. However, manufacturers have to deliver faster the product with shortened product design and production phases. The eras of prototyping in the product design can take a long time and sometimes it can surpass the budget or even worse the products need to be launched before enhancing the design phase, showing the need for rapid prototyping (De Backer et al., 2005). Rapid manufacturing uses a range of methods that are used to produce a 3D scale model of physical assembly rapidly and efficiently. It is a natural and complementary technique, as 3D printing, or additive manufacturing does not require any tooling and tolerates almost limitless freedom of shape. Since the same equipment can be used to manufacture the prototypes with different properties and materials, the rapid manufacturing provides the developer, manufacturer, development team and researchers with distinct advantages such as saving time and money because the different setup and tooling are not required. Also, with rapid manufacturing, the process may apply for repeated designs and improvements that allow the product to be evaluated and checked. This iterative cycle includes a roadmap for end-product production and refinement.

In a short period, incremental sheet forming (ISF) is considered a great alternative of consideration from the major manufacturers to reduce production costs, increases product quality and minimize manufacturing lead time. Manufacturers realized that ISF could substitute the conventional methods of sheet metal forming in traditional manual labor, decrease production costs, increase productivity, and enhance the quality of the products (Lu et al., 2015). As a result, the incremental sheet forming process could rapidly replace conventional methods in the sheet metal forming process. The ISF process is a modern approach for fabrication of sheet metals using step-by-step movement of forming tool to the workpiece without the need of dies or molds, which costs in terms of time and money. This process is performed by a forming tool that forms the sheet in a series of localized incremental deformation.

The utilization of robots in the industry encourages the researchers to investigate the potential of industrial robots for performing the ISF process instead of using a computer numerical control (CNC) machine. Due to the dynamic working diversity of industrial robots, the ability of ISF process to create a greater and complex workpiece can be enhanced. However, the robot-based ISF process has yet to be fully optimized and accepted in the industry. Behera et al. (2017) reported that the major companies such as Ford Motor are interested in the prospect of robot-based ISF process since the automotive, transportation and aerospace industries often require the use of robot for larger components, which the CNC machine has a limitation on the working range. This technology also has a great potential to be utilized in Industry 4.0, since it can offer an integration of robot, intelligence-based monitoring and control system with internet-of-things (IoT) devices and networks for cyber-physical systems (Paniti, 2014; Sa de Farias et al., 2014). Therefore, the robot-based ISF is an alternative technique in fabricating sheet metal into final products based on appropriate parameters involving robot speed, step size, wall angle, shape and size of the forming tool compared to CNC machine which is involved with feed rate, tool path and lubrication conditions on the workpiece.

In general, tool wear is a tool failure. Tool wear plays an important role in shaping both ease of forming tools and the resulting surface quality of the workpiece. One factor affecting the forming tool's failure is based on the behavior of the tool. Tool behavior is affected by many factors including the composition of the forming tool and workpiece material, the essence of the forming procedure or method and the geometry of the forming device. Many researchers are rapidly involved in developing innovative techniques for the prediction model technology and advancement in tool wear (Ambhore et al., 2015). Numerous researchers had developed the tool wear prediction modeling and mostly focused on turning (Twardowski and Wiciak, 2019) and milling (Mandal, 2014) operations, but none in the robot-based ISF process. Primarily, a proper model needs to be built and tested before implementing it for online control. The requirement to predict tool wear as a function of tool performance in the ISF process has become more important to provide a basis for a computer-based control system in the future. Nowadays, intelligent algorithms such as artificial neural networks (ANN) and fuzzy logic (FL) have been widely used to tackle the problem which cannot be satisfactorily handled by conventional analytical approaches. The advantages of intelligent algorithms include extreme computation, powerful memory, and rapid learning. Furthermore, it can predict an output parameter with accuracy even if the input parameter interactions are not completely understood. It has been reported that the implementation of intelligent algorithms could minimize the time and cost consumption during the machining process (Abellan-Nebot and Romero, 2010). These capabilities make intelligent algorithms a useful prediction tool that can be implemented successfully in the research and development of casting and molding process (Raj et al., 2021), machining process (Abellan-Nebot and Romero, 2010), joining process (Rajan et al., 2016), and shearing and forming process (Al-Musawi et al., 2020 and Meng et al., 2015).

1.1.1 Mechanism of Incremental Sheet Forming

The basic components of the ISF process are presented in Figure 1, which illustrated the workpiece, blank holder, and the forming tool. During ISF, the blank holder is used for clamping and holding the sheet in position and its opening defines the working area of the ISF forming tool. As shown in Figure

1.1(a), the flat sheet with a typical thickness of 0.3 - 2mm is held in place by a blank holder placed on the simple fixture. The basic mechanism of ISF is that a generic forming tool moves along a tool path and progressively forms a metal sheet (workpiece) into the desired shape. The tool is either moved using CNC machines or industrial robots. The metal shaping tool is a rounded single point rod, which is positioned in the collect tool holder. The shaping method traces a course as smooth gradual steps deform the sheet metal. In Figure 1.1(b), the incremental steps are shown as Δy and Δz, with the horizontal and vertical increments, respectively, thus adding up to provide a draw depth of h. There is no backup die which supports the sheet's back surface during the forming process. The application of CNC technology or industrial robots to sheet metal forming enables the replacement of costly dedicated tooling and the fast transition from the CAD model to the formed component.

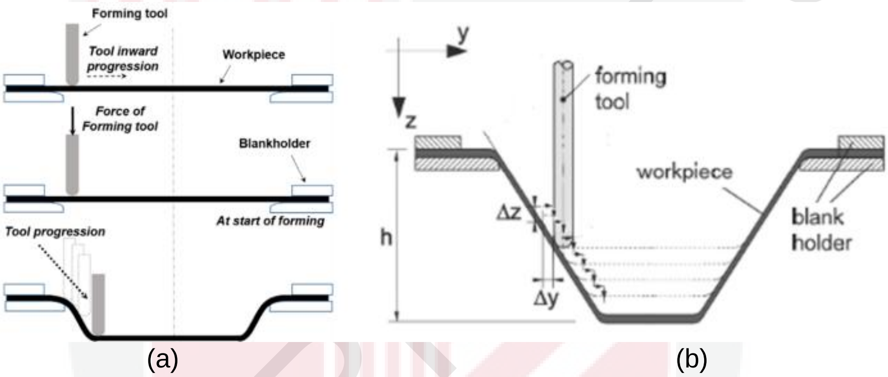

Figure 1.1 : (a) Stages and (b) incremental steps of forming tool in ISF.

1.1.2 Application of Incremental Sheet Forming

The increase in recognition of flexible forming techniques has risen to boost the interest in the ISF process (Nasulea and Oancea, 2018), whereby the complex three-dimensional profiles can be manufactured by simple jig and forming tools. The sheet metal that being deformed by a series of small, localized, and incremental deformations throughout the forming process, preventing tensile deformations in sheet metals. This is due to localized deformation, the forming forces in this process are lower than in conventional method (Liu and Li, 2019). This gives a great opportunity in reducing the volume and size of the machines engaged in this process. Malwad and Nandedkar (2014) reported the recognition of ISF as a new advanced forming technology. It includes the various advantages of ISF such as lower cost and shorter time in prototype development, enhanced formability, and easy component design modification. Also, the ISF has two key advantages that are die-less, or that it needs only a simple or cheap die and suitable for low-series output. Secondly, the formability of material is elevated and considerably often (Emmens et al., 2010).

These advantages make the ISF as a promising technique compares to the conventional sheet forming such as spinning forming or deep drawing processes for producing intricate components in rapid manufacturing. The ISF process has been widely used in the fabrication of aerospace and automotive components which are mainly built from various materials such as aluminum alloys (Ghamdi and Hussain, 2015; Wang et al., 2020), steels (Milutinovic et al., 2021; Li et al., 2017), magnesium alloys (Leonhardt et al., 2018), titanium alloys (Uheida et al., 2017; Khazaali and Fereshteh, 2016) and polymers (Shubhamkar, 2016; Sabater et al., 2018). These materials are recognized for their great strength-to-weight ratio and low formability at room temperature (Ambrogio and Gagliardi, 2015; McAnulty et al., 2017). Despite this, aluminum alloys are receiving more attention from researchers for investigating due to aluminum alloys embrace of greater toughness, meticulous thermal development coefficient, improved damping capability and enhanced high-temperature properties. Figure 1.2 shows the example of aerospace and automotive components manufactured by ISF process (Lu et al., 2013; Bambach et al., 2009, Verbert, 2010; Behera et al., 2017).

The demands technology of ISF not only in the automotive and aerospace industries, but it also has demanded from the medical industry, which the ISF technology allows the manufacturing prosthetics with exclusive characteristics for different patients (Centeno et al., 2017). Lu et al. (2015) reported that the work has been largely focused on ISF strategy and there are still considerable technical challenges to achieve better geometry precision, thickness distribution and complex cranial shape. In recent decades, versatile manufacturing solution offers by the ISF process have attracted a great deal of attention from the medical parts industry suppliers (Cheng et al., 2020). The focus is made on evaluating the feasibility of ISF to produce medical parts, and the emphasis is placed on the manufacture of a customized titanium maxillofacial implant (Grade 2) under laboratory-controlled conditions. Figure 1.3 shows the example of medical products manufactured by ISF process (Lu et al., 2015; Duflou et al., 2013; Bagudanch et al., 2015). Furthermore, Behera et al. (2017) reviewed the other application of incremental forming in various industries with the materials used as listed in Table 1.1.

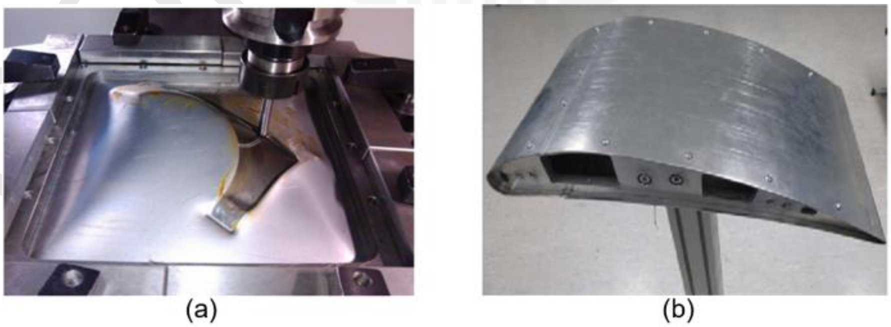

Figure 1.2 : Example of automotive and aerospace components manufactured by ISF (a) car fender and (b) airfoil
(Source: Lu et al., 2013; Bambach et al., 2009; Verbert, 2010; Behera et al., 2017).

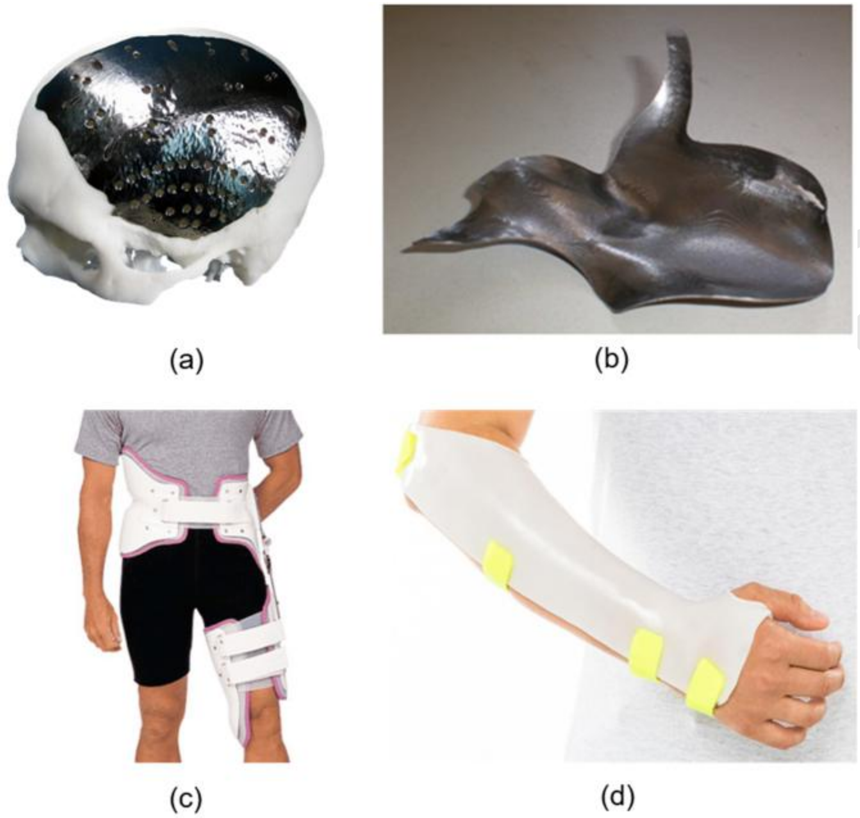

Figure 1.3 : Example of the medical parts manufactured by ISF (a) cranial plate, (b) maxillofacial implant, (c) backseat orthosis and (d) hand orthosis (Source : Lu et al., 2015; Arajou et al., 2013; Duflou et al., 2013; Bagudanch et al., 2015)**.**

Table 1.1 : Application of incremental sheet forming with different materials

Application area	Application	Material
Medical	Ankle support	DDQ steel
	Cranial plate	AA 3003
	Knee implant	Pure Ti
	Palate prosthesis	Polycaprolactone (PCL), Ti grade 2
	Cranial plate	Ti grade 2
	Knee prosthesis	Ti grade 2
	Cranial plate	Ti grade 2
	Cranial plate	Ti grade 1
	Cranial plate	PCL
	Backseat orthosis	AA 3103
	Facial implant	Ti grade 2
Architectural	Sandwich panel	Multiple
Forming equipment	Dies and moulds	Al alloy
	Dies and moulds	DC01, AA 3103
Automotive	Car body	Al alloy
	Car fender	AA 3103
	Car fender	DC04
	Car tail light	DC04
Transportation	Shinkansen (Bullet Train)	-
Aerospace	Airfoils	AA 5754

(Source: Behera et al., 2017)

1.2 Problem Statement

Recently, the diversification from CNC technology to robot-based technology has rapidly enhanced and the increasing demands of process automation for unmanned manufacturing fascinated many researchers in the field of on-line monitoring of machining processes. Because of this, extensive research work is captivating place worldwide in the area of on-line tool affects the tool life. Tool life is primary importance in material processing remaining to its direct effect on the surface quality of the machined apparent, its dimensional accuracy, and as a result of the economics of machining processes (Ambhore et al., 2015).

The improvement of ISF process performance and increasing the tool life are two critical issues that should be more developed. To improve the ISF process performance, a comprehensive study on the correlation between associated physical processes of the ISF process and mechanical behaviors of the process parameters is necessary. With multi-parameters influencing the process, it is important to determine the different changes that may have occurred during the process when manipulating the process parameters. Therefore, an optimal degree of process parameters for the procedure to be conducted needs to be taken. Conventional methods of experimental design are too complicated, and not convenient to be used. This research seeks to optimize process parameters settings. The optimal process parameters can be derived using a simple, accurate, and systematic method.

Many researchers have improvised on the ISF technology, which focuses on processing parameters and their influences (Kumar and Gulati, 2018; Lu, 2016; Gatea et al., 2016), wall thickness distributions (Choi and Lee, 2019; Mohammadi et al., 2016; Lu, et al., 2016), springback effect (Abeyrathna et al., 2017; Zhang et al., 2020), formability (Pandivelan and Jeevanatham, 2015; McAnulty et al., 2017) and surface quality (Mohanty et al., 2018; Zhai et al., 2020) but none in tool wear condition monitoring. Tool wear is one of the noticeable parameters in all of the manufacturing processes (Adnan et al., 2015). Since tool wear affects the characteristics and tolerances, which are achievable, it is a significant concern that must be received more attention (Oliaei et al., 2016). Prediction of tool wear has been a crucial topic in determining the tool life (Kong et al., 2018). According to the authors, tool wear status is one of the most important variables in ensuring the dependability and stability of a manufacturing system, because excessive wear of cutting tools causes a sharp increase in cutting force and even machine tool noise. Furthermore, tool failure accounts up to 20 % of downtime in modern processes, resulting in lower productivity. Wang et al. (2020) stated that when dealing with a physical problem, the existing prediction model frequently encounters difficulties. Physical consistency is lacking in current prediction models due to the lack of representation of physical concerns. In addition, the size of the training sample limits the performance of data-driven model. Due to the dynamic and complex working conditions, manually altering parameters in practice can add a significant cost to current prediction models. The ability to accurately predict the tool wear during machining is an incredibly important part of the diagnostics that results in the tool being replaced at the right time. Efficient tool wear assessment improves process productivity and enables replacement of the tool before unpleasant wear occurs (Twardowski and Wiciak, 2019). Rao et al. (2014) described the cost of tooling as an important factor that should be reduced to minimize the cost of manufacturing. The authors defined that tool failure can be observed by higher power consumption, poor surface finish, dimensional inaccuracy, presence of a burning band on the machine surface, tool, and workpiece vibration. In protecting the tool life, Pandiyan et al. (2018) stated that many researchers studied, evaluated and developed prediction modeling for the tool condition. However, no studies have been found for the prediction of tool wear in the robot-based ISF process.

Until now, the tool condition monitoring is intensively carried out in CNC turning and milling processes. In the turning process, a tool condition monitoring strategy based on a large number of signal features in the rough turning, where the signal feature can be extracted from the time domain signals as well as from frequency domain transform and their wavelet coefficients (time-frequency domain) (Kuntoglu and Saglam, 2021). In milling processes, tool condition monitoring is widely investigated either using vibration or force sensor. The performance of clustering methods on high-speed end milling experimental data in which the clustering methods were applied to wavelet features of force and vibration signals to illustrate the results repeatability was demonstrated (Torabi et al., 2016). In the ISF process, Behera et al. (2017) had review that the variability of the applied forces in incremental sheet forming is one of the major problems in sheet failure prediction. In addition, the prediction of applied force values was developed for optimizing tool and fixture design and correct machine-selection. Jauregui et al. (2018) investigated tool wear estimation using a neuro-fuzzy model, indicating that evaluation using simply the force signal is less accurate owing to bandwidth limitations. This flaw is mitigated by the addition of the acceleration and AE sensors, which expanded the measurement bandwidth needed to capture additional tool wear characteristics. From this point of view, an effective detection system needs to be established for the ISF process and subsequently could be used in developing a prediction model of tool wear and product quality.

Tool wear modeling can be predictive offline by using computer-based process models that utilize feedback information from the machining process. Many studies have been carried out to develop various mathematical models for the prediction of tool wear (Pimenov et al., 2017; Okokpujie et al., 2018). However, it is not easy to apply this conventional technique to practical situations because the relationship between the ISF process and the tool wear is complex. Conventional control techniques, such as PID controllers based on mathematical models cannot provide a reliable solution when global control was required. The high complexity of forming processes has become a major handicap, and the creation of global controllers capable of sustaining stable processes such as deep drawing processes which are highly non-linear forming processes, and their behavior is very difficult to describe by mathematical models (Meng et al., 2015).

According to the issues mentioned above, the studies on parametric optimization, surface characterization and prediction of tool wear in robot-based ISF process are needed to carry out. In sequence, the issues need to be given a high consideration in this research hypothesis are listed below:

1. The quality of formed surface could be improved by proper selection of process parameters, hence a parametric optimization may improve the surface quality and process productivity.

2. Since the tool condition monitoring plays a vital role in process performance, a robust detection system with reliable pattern recognition on tool wear and product quality need to be developed.

3. The relationship between tool wear and product quality with machining signals is necessary to be establish for tool condition monitoring.

1.3 Research Objectives

The main objective of this research work is to develop and compare several intelligent algorithms for tool wear prediction in robot-based ISF. To achieve this aim, the present research objectives can be listed as follows:

1. To determine the optimization of process parameters in robot-based ISF by evaluating the surface quality.

2. To evaluate the vibration signals for identifying and categorizing the tool condition and surface quality of the formed workpiece.

3. To develop AI-based predictive models such as neural networks (ANN), fuzzy logic (FL), and an adaptive network-based fuzzy inference system (ANFIS) by correlating the vibration signals with tool wear and surface roughness of workpiece in robot-based ISF.

1.4 Significance of the Study

The conventional sheet metal forming process relies on molds and dies, which are the costs of time and money. Because of these factors along with growing variants and types of sheet metal manufacturing, the highly versatile forming process is being developed. On the other hand, tool wear condition monitoring is more suitable from a technological point of view, and the development of the prediction model offers a perfect method for economic optimization of machining operation and avoidance of devastating tool failure.

Tool wear is a significant factor that affects the surface finish, development time and economy of tooling (Mali et al., 2017). In this era of high-speed machining and competitive market, continuous monitoring of tool condition is required to maintain the finished product quality. With an appropriate prediction system for tool wear conditions, a damaged tool can be replaced in time to prevent unpredicted downtime and scrapped workpiece. Appropriate sensors play a major role in obtaining the process parameter. Without the signal from this sensor, decision-making to generate the prediction monitoring system is difficult. Most researchers used a variety of methods to track the wear condition of each tool series, such as selecting process parameters, extracting features, selecting features and classifying features. However, advanced signal acquisition and processing techniques need to be developed to carry out the extraction of the functionality without affecting the process parameters.

The findings of this study are expected to contribute by offering a practical technique to analyze the vibration signal with effective pattern recognition for development on prediction modeling of tool wear in robot-based ISF. They are also providing a significant approach in tool condition monitoring system to minimize downtime related to tool damaged and affected the quality of the workpiece.

1.5 Scope and Limitation

Robot-based ISF has more advantages compared to the CNC machine, but it also has a limitation on material thickness. Robot-based ISF is not as rigid as a CNC machine. Due to the hard-to-form materials such as materials with a high yield stress, springback characteristic and surface properties which increase the friction between the forming tool and the workpiece, it will require high forming forces which not suitable for robot mechanism. The scope of this research is not limited to develop the prediction models of tool wear, which has not yet been fully studied in previous research works. It also covers the optimization of process parameters and pattern recognition of tool wear and workpiece surface roughness, which are important before the study of tool wear.

1. The process parameters are robot speed, step size and wall angle. These parameters range are selected based on the capacity and capability of the six-degree-of-freedom robot.

2. Parametric optimization is conducted by evaluating the surface roughness as a single output response using Taguchi method. The optimization experiment only utilizes aluminum alloy as a workpiece since it is the softer material and become a benchmark material.

3. Difficulty on measuring voltage or current due to the hardware condition (fragile/rot) of robot electrical parts which is obsolete in terms of input/output/controller module and complete electrical drawing not available which if wrong tapping the input output module can make the module short circuit, and unaffected temperature to the process, which is the temperature different can only be observed by using SEM analysis.

1.6 Structure of the Thesis

The thesis presents the research work on tool wear prediction in robot-based ISF, and it consists of five chapters. Contents of each chapter are briefly described as follow:

Chapter 1 introduces the background and motivation of the research, basic mechanism, and applications of the ISF. Problem statements, objectives and scope of research are also mentioned in this chapter.

Chapter 2 reviews the previous works that related to the ISF process. It includes an overview of ISF process, tool wear, signal processing and AI-based predictive modeling for tool wear. It comprehensively reviews the important parameters and process flow on the development of prediction models in tool wear.

Chapter 3 describes the methodology implemented in this research. It includes the materials used and the design of experiments. The main equipment's employed for experimental work are explained including the measuring devices and engineering software to design and generate the prediction model of tool wear. The vibration analysis and feature extraction for signal processing and development of AI-based models are also presented.

Chapter 4 discusses the experimental and modeling results. Experimental results cover the parametric optimization, pattern recognition of forming tool and workpiece surface roughness and signal collection. In this chapter also the results of signal processing and AI-based predictive models are analyzed. Then, the comparison between predictive models is compared and discussed and model validation are also being verified.

Chapter 5 presents the overall conclusions of this research work. The main contribution of this thesis on the development of the predictive models on tool wear in robot-based ISF and some recommendations for future work are stated in this chapter.

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